

# Number of Bank Agencies and Bank Credit Supply in Waemu Zone: A Spatial Econometric Approach

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## Abstract

This study examines the effect of the spatial dependence of the number of bank branches on the supply of credit in West African Economic and Monetary Union (WAEMU) countries, over the period 1995-2021. Methodologically, we mobilize spatial econometric techniques to take into account the spatial interdependence between the various countries involved in the analysis. Results from the SDM (Spatial Durbin Spatial) model reveal that the number of bank branches has a positive and significant influence on credit supply. In addition, bank size has a positive effect on credit supply. Nevertheless, inflation hurts the credit supply. Considering spatial effects has also shown us that the supply of credit from one country to another also depends on the volume of credit it receives from other countries. In terms of economic policy implications, banks in the zone need to promote the strategy of geographic expansion of their bank branches. Similarly, monetary authorities need to make efforts to keep inflation rates at moderate, stable levels, and encourage the emergence of large banks.

**Keywords:** Spatial dependence, number of bank branches, credit offer, SDM

## 1. Introduction

Since the 1990s, the banking network in the WAEMU zone has evolved, with the emergence of national banks and pan-African banks. Competition has become intense with the multiplication of bank branches. In theory, the opening of new branches enables banks to diversify risk, increase profit, and capture new customers (Boyd & Smith, 1992). Branch expansion is therefore an element of geographic diversification for banks. However, the authors are not unanimous on the beneficial effects of geographical diversification. According to Diamond (1984), geographic diversification helps reduce risk when intermediation is efficient. For De Hass and Van (2010), geographic diversification reduces risk when banks expand into countries with good economic conditions. By forging long-term relationships with their customers in bank branches, banks improve their scoring techniques, resulting in economies of control (Haubrich, 1989). The long-term relationships created in branches enable banks to save on information costs, which, in a banking environment marked by rate competition, should ultimately lead to a fall in the cost of credit (D'Auria, Foglia, & Marullo-Reedtz, 1999). Higher levels of geographic diversification can reduce exposure to idiosyncratic local shocks (Goetz et al., 2016) with improved economies of scale and scope (Berger & De Young, 2001). Reasons for branch opening include deregulation (Yildirim & Mohanty, 2010) and factors related to bank size and profitability (Regehr & Sengupta, 2016). In addition, regulatory and tax arbitrage opportunities, access to markets offering better growth prospects, and the internalization of existing customer-bank relationships are some of the reasons put forward to explain higher levels of foreign branch opening (Focarelli & Pozzolo, 2005).

Conversely, Goetz et al. (2013) argue that geographical diversification accentuates agency problems, due to the distance created between the bank and its subsidiaries. Such distance can only lead to an increase in banking risks. And yet, it is widely accepted that a decrease or increase in risk can influence the supply of credit. We can therefore establish correlations between the spatial dependence of bank branches and the supply of credit. This correlation between the number of branches and credit supply, if it exists, is referred to as spatial dependence.

In the WAEMU zone, deregulation in the banking industry has led to the removal of barriers, facilitating the massive entry of new banks and the distribution of bank credit. According to BCEAO annual reports, credit to the economy as a percentage of GDP has risen from 25.9% in 2017 to 26.8% in 2021, in the WAEMU zone.

Outstanding bank credit rose from 12633.2 billion CFA francs in 2017 to 17781.2 billion CFA francs in 2021, an increase of 40.74%. In 2018, banks managed around 2,542 branches, 3,000 ATMs, and 10,300,000 customer accounts. Between 2018 and 2020, the number of bank branches rose from 3,629 in 2018 to 3,762 in 2020, an increase of 3.66%. In the UEMOA zone, it seems that bank credit is growing faster than the number of bank branches. However, at the country level, the reality is quite different. In Côte d'Ivoire, the powerhouse of the zone, the number of branches rose from 281 in 2008 to 692 in 2017, an increase of 140%. As for bank loans, over the period 2012-2017, they expanded, evolving at a medium-term credit rate of 20% to reach 5900 billion FCFA in 2017. It seems that in recent years, bank branches have grown much faster than outstanding loans in this country. In Senegal, the number of branches rose from 498 to 512 between 2018 and 2019, an increase of 3%. Meanwhile, credit granted to the private sector rose from 4,596.7 billion FCFA in 2019 to 4,275 billion FCFA, in 2018, a relative increase of 6%, according to the Banking Commission's 2019 report. In Senegal, these figures give the idea of a stronger progression of outstanding loans compared to that of bank branches.

Based on this ambiguous observation, this paper attempts to answer the following questions: to what extent has, the spatial distribution of bank branches influenced the supply of credit in the WAEMU zone? To answer this central question, it will be necessary to answer other more specific ones, namely: what is the effect of the number of bank branches on credit supply? And what is the effect of bank size on credit supply? Thus, this article aims to analyze the effect of spatial dependence of bank branches on credit supply in the UEMOA zone. To do so, the following two specific objectives need to be met: (i) to determine the effect of the number of bank branches on credit supply and (ii) to identify the effect of bank size on credit supply.

To achieve our objectives, we make the following assumptions. The first is that geographic diversification of bank branches increases credit supply. The second is that increasing bank size has a positive influence on credit supply.

In terms of contribution, this study provides empirical knowledge on the link between the number of bank branches and the supply of bank loans in the WAEMU zone. Moreover, to our knowledge, no study has addressed the relationship, in terms of spatial dependence, between the number of bank branches and the supply of credit in the UEMOA zone. Thus, our study aims to fill the gap in this literature by relating bank branches and credit supply in terms of spatial dependence.

Methodologically, the study is based on spatial econometrics developed by authors such as Anselin et al. (1997), specifically the SDM model.

The remainder of the article is structured as follows. The second section presents the literature review on spatial dependence and credit supply. The third section presents the methodology and a description of the variables used. The fourth section deals with data sources and descriptive analysis. The fifth section presents the estimation results and the sixth section is a conclusion.

## 2. Literature Review

This section reviews theoretical and empirical contributions on the relationship between spatial dependence and credit supply.

### 2.1 The Review of Theoretical Literature

From a theoretical point of view, the theoretical contributions focus on two key issues. Firstly, geographical diversification and credit supply, and secondly, the spatial effects of bank branches on credit supply.

According to Diamond (1984), geographical diversification increases the intermediary's risk tolerance for each loan, thereby reducing the cost of risk-taking. Geographical diversification can therefore reduce banking risk when banks take advantage of the economic situation of individual countries. Indeed, when banks locate their branches in countries with strong economic growth potential, they reduce risk to the extent that borrowers will have sufficient resources to repay their loans (De Hass & Van, 2010). In the same vein, Aguirregabiria et al. (2016) assert that banks open branches in several countries to diversify risk geographically. Conversely, according to Goetz et al. (2013), the geographical expansion of banks creates a distance between banks and their branches, which would be at the root of certain problems in the banking sector, notably the difficulty of controlling branch managers. Geographic diversification would therefore accentuate agency problems, as managers could manipulate their performance evaluation tools, particularly accounting, to maximize their wealth (Ross et al., 2016).

Concerning the spatial effects of bank branches on credit supply, the geographical expansion of bank branches leads to a geographical concentration of banking activity, and therefore of credit, creating a spillover effect. In addition, there is a specificity, attributed by the banking literature, to local banks compared to nationwide banks

(Panizza & Presbitero, 2013). Local banks would be both more involved in supporting their respective markets, and more resilient in the event of a crisis, but also more dependent on these markets because they are less geographically diversified and therefore rely more heavily on the collection of local deposits.

For their part, Bolton et al. (2013) show that, in the event of an unfavorable situation, local banks, through relationship lending, would enable borrowers to benefit from a higher level of credit compared to the transactional lending of nationwide banks. On the other hand, remote banks would have an incentive to develop standardized credit activities and focus on large companies, leaving the use of relationship lending and the SME credit segment to local banks (Liberti & Petersen, 2019).

## 2.2 The Empirical Contributions

Empirically, the spatial dependence relationship between geographic diversification and credit supply is the subject of empirical work in both developed and developing countries. Algeri et al. (2023) investigate the presence of spatial dependence in the non-performing loan (NPL) ratio of small Italian cooperative banks, over the period 2011-2017. Using spatial econometrics techniques, they demonstrate that spatial and spatio-temporal variables drive bad loans in local banks. Olivares et al. (2021) devoted a study to extending standard credit rating models by taking into account spatial dependence on credit risk. Using data from a large microfinance covering 240 counties in 20 Chinese provinces, from January 2017 to July 2018, they find that the inclusion of spatial random effects improves the ability to predict defaults and non-defaults of individual and group loans. Calabrese et al. (2017) have shown how binary spatial regression models can be exploited to measure contagion effects in credit risk arising from bank failures. Using different specifications of the interbank connectivity matrix, they estimated a contagion parameter for Eurozone banks between 1996 and 2012. This provides evidence of high levels of systemic risk due to contagion during the European sovereign debt crisis.

In India, Sharma and Anand (2020) examine how geographic diversification affects the performance of Indian banks over the period 2001 to 2016. Using a fixed-effect model (FEM) with a distributed lag, they indicate that, for foreign and state-owned banks, geographic diversification helps to increase bank returns but has no significant impact on bank risk.

In the WAEMU, the only study to focus on spatial dependence on credit supply is Tanimoune (2005). The author examines the effects of spatial autocorrelation on the distribution of bank credit in the WAEMU. He concludes that there are spatial dependence effects in the estimation of credit distribution. However, the author confined himself to examining the influence of three variables: GDP per capita, a composite financial development indicator, and the policy rate on credit granted to the private sector as a proportion of GDP. Our research extends and deepens this empirical literature.

## 3. Spatial Econometric Methodology and Estimation Procedure

We present the methodology of spatial econometrics and the estimation procedure in turn.

### 3.1 Spatial Econometric Methodology

To describe spatial heterogeneity, a linear relationship for the spatial cross-section data model was considered as follows:

$$y_i = w_i\beta_i + \varepsilon_i \quad (1)$$

To describe spatial heterogeneity, a linear relationship for the spatial dynamics panel data model was considered as follows:

$$y_{it} = w_i\beta_{it} + \varepsilon_{it} \quad (2)$$

where  $i$  refers to the countries of the study at  $i=1, \dots, n$  points in space,  $t$  is the period at  $t=1, \dots, m$ ,  $W$  represents a matrix of explanatory variables (distance) with a set linked from  $\beta_i$  and  $\beta_{it}$  parameters,  $y_i$  and  $y_{it}$  (bank credits) are the dependent variables at country (or location)  $i$  and time  $t$ , and  $\varepsilon_i$  and  $\varepsilon_{it}$  indicate a stochastic disturbance (random error). Equations (1) and (2) represent the simple spatial cross-section data model and the simple spatial dynamic panel data model, respectively. With the geographically weighted regression (GWR) method, as shown in equation 3, bank credit is represented by  $y$  where  $N \times 1$  vector of dependent variable observations are collected at  $n$  points in space,  $N \times K$  matrix of explanatory variables and  $\varepsilon_i N \times 1$  is a vector of normal errors, which has a constant variance. Given  $w_{ij}$  represents an  $N \times N$  diagonal matrix containing weights based on the distance between country  $i$  and other countries, the GWR model can be as follows:

$$w_{ij}y = w_{ij}X\beta_i + \varepsilon_i \quad (3)$$

In the present research, four models were used for the spatial panel data model (SAR, SEM, SAC, and SDM).

SAR is the spatial lag model, also known as the spatial autoregressive model, and SEM is the spatially autocorrelated error model. However, SAR contains endogenous interaction effects and SEM contains interaction effects among the error terms. In the study by Anselin and Bera (1998), the procedure for testing a spatial offset or spatial error model was based on robust Lagrange multiplier tests. SAC is a spatial autoregressive model with spatial error autocorrelation. Autoregressive perturbations that include both endogenous and interaction effects among the error terms. Finally, we have the Durbin Spatial Model (SDM), which includes spatially dependent variables and explanatory variables, and uses the marginal effects of explanatory variables from neighboring countries based on the SAR model. The general form of the spatial panel model is as follows:

$$y_{it} = \alpha + \tau y_{it-1} + \rho \sum_{j=1}^n w_{ij} y_{jt} + \sum_{k=1}^K x_{itk} \beta_k + \sum_{k=1}^K \sum_{j=1}^n x_{itk} \beta_k \theta_k + \mu_i + \gamma_t + v_{it} \quad (4)$$

$$v_{it} = \lambda \sum_{j=1}^n m_{ij} v_{jt} + \varepsilon_{it} \quad (5)$$

$$i = 1, \dots, n$$

$$t = 1, \dots, T$$

where  $\theta$  represents a  $K \times 1$  vector of fixed but unknown parameters to be estimated,  $\lambda$  is the spatial autocorrelation coefficient,  $\rho$  is the spatial autoregression coefficient,  $W_{ij}$  is a non-negative  $N \times N$  matrix describing the configurations or arrangement non-stochastic spatial weight matrices of the sample units which are the spatial parameters of the model,  $t = 1, 2, \dots, T$ ,  $y_{it} = (y_{it}, y_{2t}, \dots, y_{it})'$ ,  $X_{itk}$  is an  $i \times k$  matrix of non-stochastic regressors,  $X_{jtk}$  is a  $j \times k$  matrix of non-stochastic regressors,  $v_{it} = (v_{it}, v_{2t}, \dots, v_{it})'$  are  $i \times 1$  column vectors, the  $v'_{it}$  are i.i.d. between  $i$  and  $t$  with zero mean and variance  $\sigma_0^2$ ,  $\alpha$  is an  $i \times 1$  column vector of individual fixed effects,  $\tau$  is a scalar indicating a temporal effect,  $\beta_k$  is the indicator of the  $k \times 1$  vector of  $k$  parameter linked to observation,  $\varepsilon_{it}$  is the  $N \times 1$  vector of normal errors  $\mu_i$  and  $\gamma_t$  illustrate spatial fixed effects and temporal fixed effects respectively.  $\varepsilon_{it}$ ,  $\mu_i$  and  $\gamma_t$  are random variables independent of each other.  $\theta$ ,  $\lambda$ ,  $\rho$  are the spatial parameters. When  $\theta = 0$ , the model is SAC; when  $\lambda = 0$ , it is SDM; when  $\lambda = 0$  and  $\theta = 0$  we have a SAR model; when  $\rho = 0$  and  $\theta = 0$ , we have a SEM model. All models consider a weight matrix but the considered weight matrix of each model is different. The Hausman test applied to spatial models is used to check whether the individual and/or temporal effects included are indeed of a fixed or random nature (Elhorst, 2009; Bouayad-Agha et al., 2018).

### 3.2 Estimation Procedure

In the presence of spatial autocorrelation, OLS estimates are not convergent in the case of a lagged endogenous variable and are inefficient in the case of spatial autocorrelation of errors (Le Gallo, 2002). To find convergent and efficient estimators, the most commonly used methods are maximum likelihood, instrumental variables or generalized moments. Indeed, according to Le gallo (2002), the instrumental variable (IV) method is best suited when certain explanatory variables are correlated with the errors (SDM model). The maximum likelihood method, on the other hand, is used when there is a lagged endogenous variable (SAR) when the autocorrelation is at the level of the error terms (SEM), or in the case of a SAC model. In addition, a test of inter-individual dependence is required, and several tests have been proposed, including those of Pesaran (2004) and Breusch-Pagan (1980). The Pesaran (2004) test is used for micro-panels, i.e. when the temporal dimension is smaller than the individual dimension ( $T < N$ ). Otherwise, the Breusch-Pagan test is appropriate. Since our study has a temporal dimension (15 years) greater than the individual dimension (8 countries), we will consequently use the Breusch-Pagan (1980) test for the analysis of independence between the different observations. Furthermore, to test for the presence of spatial autocorrelation, several tests are proposed, namely Moran's Index (I) test and maximum likelihood-based tests such as the Likelihood Ratio (LR), Wald Ratio (W), and Lagrange Multiplier (LM) (Anselin, 1988; Burridge, 1981). The autocorrelation test is used to test for the presence of interdependence between the different variables or between the model's error terms. Moran's (1950) I test for the absence of spatial autocorrelation is the first specification test to have been proposed in spatial econometrics and is generally the first step in the search for the most appropriate process to represent the data. However, this test does not indicate the potential form of autocorrelation. To overcome this shortcoming, the Lagrange Multiplier (LM) approach is the most widely used, as it provides a more explicit spatial specification (Anselin, 1988).

## 4. Empirical Specification and Data

The specification of the empirical model is presented before the descriptive analysis of the variables.

### 4.1 Specification of the Empirical Model and Description of the Variables

The spatial model of this study is inspired by the Goetz et al. (2016) respecified in the functional form as follows:

$$Credit_{it} = f(HHI_{it}, GDP_{it}, CPI_{it}, deposit_{it}, size_{it}, agencies_{it}) \quad (6)$$

In its econometric form, equation 6 is as follows:

$$Credit_{it} = \alpha_i + \alpha_1 HHI_{it} + \alpha_2 GDP_{it} + \alpha_3 CPI_{it} + \alpha_4 deposit_{it} + \alpha_5 size_{it} + \alpha_6 agencies_{it} + \varepsilon_{it} \quad (7)$$

$i = 1, \dots, 8$  represents the UEMOA countries

$t = 1995, \dots, 2021$  represents the time or period of the study.

Where,  $GDP$  represents GDP per capita, deposit represents the amount of deposits,  $size$  represents the size of banks,  $agencies$  represents the number of bank branches,  $HHI$  represents the Herfindahl-Hirschman index,  $CPI$  represents the consumer price index consumption,  $Credit$  to the economy and  $\varepsilon$  represents the error term.  $\alpha_i = 0 \dots 7$  represents all the parameters to be estimated.

As far as the variables are concerned, we need to distinguish between explained and explanatory variables. The dependent or explained variable at the heart of our study is bank credit. Here, we focus on credit to the economy, i.e. all lending by banks, credit institutions, and the Central Bank to businesses and households (CREDIT). Credit to the economy is measured by the logarithm of total loans. Regarding the independent variables, the variable of interest is the number of bank branches (AGENCIES). In the literature, we find that the relationship between the number of bank branches and the supply of credit is positive. We therefore expect the coefficient associated with this variable to have a positive sign. Apart from the interest variable, we have the consumer price index (CPI), which measures changes in the average price level of goods and services consumed by households. The index measures inflation over a given period, and therefore the evolution of the value of money. We therefore expect the coefficient associated with this variable to have a negative sign. In addition, we have the bank size variable (SIZE), which is measured here by the logarithm of total bank assets. Bank size is an important variable in determining the supply of credit. Baselga-Pascual et al. (2015) argue that large banks run less risk, and are therefore able to distribute more credit. We therefore expect the coefficient associated with this variable to have a positive sign. To assess people's standard of living, we use GDP per capita (GDP). The higher the standard of living, the more borrowers will be able to repay loans. As a result, we can expect a positive sign for the coefficient associated with this variable. We use bank deposits as another control variable (DEPOSIT). It is perceived as the share of income that is not consumed and deposited in the bank. It is captured here by the logarithm of the sum of deposits in the WAEMU zone. Kolapo and Olaniyan (2018) also used this variable. In theory, if banks are playing their banking intermediation role well, then an increase in deposits should translate into easier credit (Mairafi et al., 2018). We therefore expect a positive sign for the coefficient associated with this variable. Finally, we use an indicator that measures bank concentration. For this, we use the Herfindahl-Hirschman Index (HHI), an index measuring market concentration, i.e. the number of firms producing a good or providing a service. The relationship between HHI and credit supply is positive in the literature. Table 1 summarizes the study variables and the expected signs of the associated coefficients.

Table 1. Expected signs for variables

VARIABLES	DEFINITION OF VARIABLES	EXPECTED SIGNS	SOURCES
AGENCIES	Number of bank branches	(+)	BCEAO
GDP	$GDP \text{ per capita} = \frac{GDP}{Total \text{ population}}$	(+/-)	BCEAO
CPI	Consumer Price index	(+/-)	WDI
HHI	Herfindahl-Hirschman index $HHI = \sum_{i=1}^n s_i^2$	(+)	WDI
DEPOSIT	Deposit amount Log (deposit)	(+)	BCEAO
SIZE	bank size log (bank asset)	(+)	WDI
CREDIT	Credit to the economy log (total loans)	(+)	BCEAO

Source: constructed by the author using data from (WDI, 2022) and (BCEAO, 2022).

Our study covers the period 1995-2021 and is based on a panel of 8 WAEMU countries. The data comes mainly from the World Bank (WDI, 2022) and the Central Bank of West African States (BCEAO, 2022).

#### 4.2 Descriptive Analysis of Variables

Table 2 shows the descriptive statistics of the data. The value of the average credit rate is 5.51, with a low dispersion around the mean of 0.82, with a minimum of 0.71 and a maximum of 6.64. Concerning the number of

bank branches, the value of the average rate is 199.6125 with a dispersion around the mean of 225.9138, a minimum of 3, and a maximum of 1321.

Table 2. Descriptive statistics for variables

Variables	Obs	Mean	Std	Min	Max
CREDIT	216	5.518552	0.8203193	0.7160033	6.648885
AGENCIES	216	199.6125	225.9138	3	1321
GDP	216	2.792541	2.842459	0.0074282	29.41329
CPI	216	85.73523	19.5628	30	110.8
HHI	216	2.599491	1.155611	2.52	3.434768
DEPOSIT	216	4.623846	0.5574842	2.242044	5.338119
SIZE	216	5.938982	0.6002143	4.146004	6.932868

Source: Author based on WDI data (2022).

The number of bank branches varies greatly from one country to another. As for GDP per capita, the average value is 2.79, with a relatively low dispersion of 2.84, a minimum of 0.0074, and a maximum of 29.41. Over the study period, the countries' living standards are not very far apart. For the CPI, the value of the average rate is 85.73, with a dispersion around the mean of 19.56, a minimum of 4.59 and a maximum of 110.8. Inflation is highly variable within the zone. For the Deposit, the value of the average rate is 4.62 with a low dispersion of 0.55, a minimum of 2.24 and a maximum of 5.33. For the Size variable, the average rate is 5.93, with a small dispersion of 0.60, a minimum of 4.14, and a maximum of 6.93. In virtually all countries, we find the same types of banks and the same deposit-taking behavior. As for the structure of the banking market, the average value of the HHI is 2.59, with a small dispersion of 1.15, a minimum of 2.52, and a maximum of 3.43. This descriptive analysis has enabled us to analyze and statistically describe the different variables in our model. Let's now analyze the correlation matrix to judge the quality of the correlation between the different variables in the model. The results of the correlation matrix for the respective variables are also shown in Table 3.

Table 3. Correlation matrix

Variable	CREDIT	AGENCIES	GDP	CPI	HHI	DEPOSIT	SIZE
CREDIT	1.000						
AGENCIES	0.443*	1.000					
GDP	-0.075	-0.028	1.000				
CPI	0.491 *	0.374*	-0.258*	1.000			
HHI	0.210	0.240*	-0.114	0.320*	1.000		
DEPOSIT	0.769 *	0.347*	-0.092	0.498*	0.206*	1.000	
SIZE	0.914*	0.479*	-0.111	0.610*	0.217*	0.812*	1.000

Source: constructed by the author using data from (WDI, 2022) and (BCEAO, 2022)

Note. (\*) represents the level of significance at the 5% level.

A correlation matrix is a table that displays the correlation between variables. According to this matrix, the variables agencies, CPI, HHI, Deposit, and size are positively correlated with credit. However, there is a negative correlation between GDP and bank credit, then between GDP and the consumer price index. Given the relevance of the variables (agencies, CPI, HHI, Deposit, size) in the economic literature, they are retained for the estimations. Furthermore, the correlation matrix shows high values, sometimes exceeding 0.80. As a result, these high correlations between several explanatory variables can pose a problem in estimating and interpreting a model. To remove any doubts, we apply the VIF Test, the results of which are shown in Table 4.

Table 4. Multicollinearity test (VIF)

Variables	VIF	1/VIF
SIZE	3.93	0.254442
DEPOSIT	2.99	0.334073
CPI	1.79	0.559610
AGENCIES	1.40	0.714692
HHI	1.14	0.874863
GDP	1.08	0.925317
Mean VIF	2.06	

Source: constructed by the author using data from (WDI, 2022) and (BCEAO, 2022).

Analysis of the VIF values of the variables allows us to assert that there is no problem with multicollinearity. Indeed, according to Gujarati et al. (2009), if the VIF value is greater than 10, then there is strong multicollinearity. The results in Table 4 indicate that none of the VIF values is greater than 10, ruling out any multicollinearity problem. In the following, we present the usual econometric tests and select the model to be interpreted.

## 5. Empirical Results

This section first presents the results of the econometric tests, before moving on to the estimation results.

### 5.1 Preliminary Econometric Tests

Preliminary tests include homogeneity and dependency tests.

- **The homogeneity test**

The very first thing to check when using a panel data sample is whether the data-generating process is homogeneous or heterogeneous. This means testing the equality of the coefficients of the model studied in the individual dimension, and checking whether it is appropriate to assume that the theoretical model studied is the same for all countries (model pooled), or specific to each country (Hurlin and Mignon, 2006). Under the null hypothesis, the panel is homogeneous, and under the alternative hypothesis, the panel is heterogeneous. The results in Table 5 reject the hypothesis that the panel is homogeneous at the 5% threshold. We conclude that the panel is heterogeneous. We perform the Hausman test to check whether the specific effects are fixed or random. This will enable us to choose the appropriate inter-individual dependence test.

Table 5. Results of Fisher homogeneity test

F (6, 207) = 187.34
Prob > F = 0.0000

Source: Author, based on BCEAO data (2022).

- **Fixed or random effect model**

To check whether the model is a random-effect model or a fixed-effect model, we perform the Hausman test adapted to spatial models. The null hypothesis is the presence of random effects. The test results in Table 6 show that there is a fixed effect, as the test probability is less than 1%.

Table 6. Hausman test

TEST	Statistics	P-value
Hausman LM Test	19.21	0.0038

Source: Author, based on BCEAO data (2022).

As a result, it is preferable to use a mixed fixed-effects (FE) model, which requires us to perform the Breusch-Pagan (1980) dependency test.

- **Testing for inter-individual dependence**

Inter-individual dependence can arise as a result of a variety of phenomena, such as omitted observed common effects, spatial spillovers, unobserved common effects, or the general residual interdependence that could remain even when all observed and unobserved common effects are taken into account. In the context of our work, the study relies on the Lagrange Multiplier (LM) test of inter-individual dependence developed by Breusch-Pagan to the detriment of that developed by Pesaran (2004), insofar as our panel has a large temporal dimension (T=27) and a small individual dimension (N=8). Table 7 shows the results of the Breush-Pagan (1980) dependency test, which confirms the presence of inter-individual dependency since the probability is less than 5%. The results of these tests confirm the presence of a cross-sectional dependency.

Table 7. Breusch-Pagan (1980) and Pesaran (2015) cross-sectional dependency test

Chi2	P-value
120.813***	0.0000

Source: author, based on data from (WDI, 2022) and (BCEAO, 2022)

Note. (\*\*\*) represents the level of significance at the 1% level.

Since the test reveals inter-individual dependency, the second-generation unit root test will be appropriate.

#### • Stationarity tests

We perform second-generation unit root tests, notably those of Pesaran (2003) and Pesaran (2007). The series is stationary when the probability resulting from the test (CADF or CIPS) is below the predefined threshold (5%). Otherwise, we speak of the presence of a unit root and conclude that the series is not stationary. The results summarized in Table 8 show that the variables have a mixed order of integration. Some variables are stationary in level, while others are stationary in first difference.

Table 8. Unit root tests by Pesaran (2007) and Pesaran (2003)

VARIABLES	In level		In first difference		Decisions
	CADF	CIPS	CADF	CIPS	
AGENCIES	-2.180 (0.110)	-2.180 (0.110)	-5.115*** (0.000)	-5.115*** (0.000)	I (1)
GDP	-4.683*** (0.000)	-4.683*** (0.000)	-	-	I (0)
CPI	-1.798 (0.456)	-1.798 (0.456)	-4.301*** (0.000)	-4.301*** (0.000)	I (1)
HHI	-2.976*** (0.000)	-2.976*** (0.000)	-	-	I (0)
DEPOSIT	-3.130* (0.000)	-3.130*** (0.000)	-	-	I (0)
SIZE	-2.134 (0.138)	-2.134 (0.138)	-4.631*** (0.000)	-4.631*** (0.000)	I (1)
CREDIT	-2.481*** (0.018)	-2.481*** (0.018)	-	-	I (0)

Source: author, based on data from (WDI, 2022) and (BCEAO, 2022)

Note. The (\*\*\*), (\*\*) and (\*) indicate the level of significance at 1%, 5%, and 10%, respectively. The p-values are in brackets.

We now proceed to the spatial autocorrelation test to verify the presence or absence of spatial dependence.

#### 5.2 Diagnostic Tests for Spatial Dependence

The results of the spatial autocorrelation tests based on the Lagrange Multiplier (LM) are shown in Table 9.

Table 9. Spatial autocorrelation test of error terms (SDM)

	Statistic	P-Value
Global Moran MI	-0.0099	0.9111
Global Geary GC	0.8868	0.7599
Global Getis-Ords GO	0.0889	0.9111
Moran MI Error Test	0.0641	0.9489
LAGRANGE MULTIPLIER	LMERR (Burrige)	0.0242
	RLMERR (Robust)	7213.1441
	LMLAG (Anselin)	0.0003
	RLMLAG (Robust)	7213.1202
	LM SAC (LMERR+RLMLAG)	7213.1444
	LM SAC (LMLAG+RLMERR)	7213.1444

Source: constructed by the author using data from (WDI, 2022) and (BCEAO, 2022).

At the end of the test, we see that the value LMLAG (Robust) = 7213.1202 has a probability of less than 5%, which means that it is significant. We therefore reject the null hypothesis of no autocorrelation of errors and we say that our model contains spatially interdependent random effects. Likewise, to check whether the dependence is at the level of the dependent variable, we use the LMLAG test (Anselin). Given that the p-value of LMLAG (Anselin) = 0.9853, we accept the null hypothesis and conclude that there is no interdependence between the dependent variables of the different countries.

#### 5.3 Estimation Results and Discussion

We will present in Table 10, the summary of the results of the 4 models. These are the SDM, SEM, SAC, and SAR models.



Table 10. Results of the SDM, SEM, SAC, and SAR models

VARIABLES		(1) SDM	(2) SEM	(3) SAC	(4) SAR
AGENCIES		0.008** (0.045)	0.008** (0.039)	0.008** (0.050)	0.008** (0.049)
PIB		0.002 (0.706)	0.002 (0.800)	0.002 (0.800)	0.001 (0.807)
CPI		-0.003** (0.011)	-0.004*** (0.001)	-0.004*** (0.001)	-0.004*** (0.001)
HHI		0.020 (0.517)	0.026 (0.189)	0.025 (0.210)	0.023 (0.248)
DEPOSIT		0.080 (0.257)	0.075 (0.292)	0.075 (0.292)	0.078 (0.269)
SIZE		1.265*** (0.000)	1.254*** (0.000)	1.254*** (0.000)	1.251*** (0.000)
CONS		-2.164193 (0.000)	-1.981 (0.000)	-1.981 (0.000)	-1.976 (0.000)
OBSERVATIONS		216	216	216	216
AIC		0.111	0.111	0.112	0.111
R 2 AJUSTE		0.838	0.833	0.833	0.833
Test de Moran	Global Moran MI	-0.009 (-0.112)	0.025 (0.632)	0.025 (0.632)	0.025 (0.632)
	Global Geary GC	0.886 (-0.306)	0.851 (-0.419)	0.851 (-0.419)	0.851 (-0.419)
	Global Getis-Ords GO	0.088 (0.112)	-0.230 (-0.632)	-0.230 (-0.632)	-0.230 (-0.632)
	Moran MI Error Test	0.064 (1.471)	0.128 (2.779)	0.128 (2.779)	0.128 (2.779)
	Test LM-Error	0.024	0.173	0.173	0.173
	Test LM-Lag	0.000	543.128	543.128	543.128
	Test Robuste LM-Error	7213.120	5.28	5.28	5.28
	Test Robuste LM-Lag	7213.144	5.28	5.28	5.28
	Test Facteur Commun	7213.144	5.28	5.28	5.28
	Test LM residual auto	11.742 (0.0006)	16.260 (0.0001)	16.260 (0.0001)	16.188 (0.0001)

Source: author based on data from (WDI, 2022) and (BCEAO, 2022).

At least two criteria can help in the choice of models: the Akaike information criterion (AIC) and the prediction criterion of the root mean squared error RMSE (Root Mean Squared Error). However, the RMSE has limits in its use for spatial models, which leads us to use the Akaike information criterion (AIC) to therefore choose the best model. The results recorded in Table 11 indicate that the SDM model is the one with the lowest coefficient.

Table 11. Model choice table

MODELS	SDM	SAR	SEM	SAC
AIC	0.1115	0.1121	0.1118	0.1119
RMSE	0.3301	0.3352	0.3348	0.3348

Source: author based on data from (WDI, 2022) and (BCEAO, 2022).

Our choice therefore concerns the SDM model for the interpretation of the results, which are recorded in Table 12.

Table 12. Result of SDM model estimations

Variables	Coefficient	Pvalue
AGENCIES	0.0080996**	0.045
GDP	0.0029891	0.706
CPI	-0.0039019**	0.011
HHI	0.0207642	0.517
DEPOSIT	0.0805264	0.257

SIZE	1.265857***	0.000
w1 × agencies	-5.59e-06	0.703
w1 × GDP	0.0001896	0.914
w1 × CPI	-0.000592	0.061
w1 × HHI	0.0027202	0.339
w1 × DEPOSIT	0.0025863	0.884
w1 × SIZE	0.006465	0.683
_cons	-2.164193	0.000

Source: constructed by the author using data from (WDI, 2022) and (BCEAO, 2022)

Note. (\*\*\*) represents the level of significance at the 1% level, (\*\*) at 5%, and (\*) at 10%.

The analysis of Table 12 shows that the number of agencies has a positive influence on the credit supply at the 5% threshold, while inflation (CPI) has a negative influence on the credit supply at the threshold of 5%. The size of the banks (size) positively influences the credit supply at the threshold of 1%. Large banks have a strong capacity to offer credit due to their control of risk and their ability to cope with shocks. In addition, the multiplication of bank branches allows banks to reduce information asymmetries, thus promoting the distribution of bank credit. However, inflation is not favorable to the supply of credit. Indeed, in inflationary periods, banks increase nominal interest rates, which increases the cost of bank credit, thus discouraging borrowers. Table 13 presents the direct, indirect, and total effects of SDM in the short and long term, as prescribed by Lesage and Pace (2009). Indeed, in spatial econometric models, spatial dependence makes the coefficients of the independent variables no longer appropriate to measure the influence and statistical significance of the variable, rather the effects of the independent variables on the dependent variable should be decomposed into effects direct and indirect, then the model could be explained. For country  $i$ , the direct effect measures the average impact of a variation in  $X_k$  of country  $i$  on the volume of bank credit in this same country. The indirect effect measures the average impact of a variation in  $X_k$  of the country  $i$ 's neighbors on the volume of bank credit in country  $i$ . Finally, the sum of the two effects makes it possible to obtain the total effect.

We interpret the total effects in the long run because, in the short run, the direct and indirect effects may differ. However, adjustments are made to remedy the dysfunctions.

Table 13. Direct, indirect, and total effects of SDM in the short and long term of the variables

Variables	Short term			Long term		
	Direct Effect	Indirect Effect	Total Effect	Direct effect	Indirect Effect	Total Effect
AGENCIES	-5.600*	8.890*	-5.59*	0.008**	-1.580*	0.008**
GDP	0.000	-3.010	0.000	0.002	-4.750	0.002
CPI	0.000*	0.410	-0.000*	0.003**	6.200	-0.003**
HHI	0.002	-4.320	0.002	0.020	-0.00003	0.020
DEPOSIT	0.002	-4.111	0.002	0.080	-0.000	0.080
SIZE	0.006	-0.000	0.006	1.267***	-0.002	1.265***

Source: Author, based on data from BCEAO (2022), WDI (2022) and GFDD (2022)

Note. (\*\*\*) (\*\*) (\*) represent the level of significance respectively at the threshold of 1%, 5%, and 10%.

The results show at the level of our optimal model (SDM), that in the long term, the direct and total effects of the number of bank branches on bank credit appear positive. On the other hand, the indirect effects are negative. This tells us that in the long term, the number of bank branches would lead to an increase in the supply of credit. This first result indicates that the number of bank branches increases the supply of credit, because, through its bank branches, banks manage to reduce banking risks without forgetting a possible diversification of the asset portfolio over several geographical areas. This result is similar to the prediction of Markowitz's (1952) modern portfolio theory applied to spatial economics.

At the CPI level, in the long term, the direct and total effects are significant while the indirect effects are not. The negative total effects indicate that inflation acts negatively, in the long term, on the supply of credit in the area. This second result indicates that inflation hurts credit supply in the WAEMU zone. Indeed, in an inflationary situation, banks are obliged to raise the level of nominal interest rates, therefore debtors. The demand for credit is discouraged and the supply of loans falls. This result is consistent with the study of Okaro (2016) which indicated that high inflation rates are generally associated with high interest rates on loans and a decline in credit supply.

For bank size, the direct and total effects are positive with insignificant indirect effects. The size of the bank contributes to the increase in the supply of credit in the WAEMU zone. Indeed, large banks can open bank branches to get closer to their customers. The larger a bank, the greater its profitability and the more it attracts a large number of customers to its branches. In addition, large banks have the advantage of having better risk management capacity, which increases their credit supply capacity. This result is consistent with those obtained by Beck et al. (2004).

In total, by comparing the direct, indirect, and total effects of the different variables, we note that the expansion of bank branches and the size of banks are favorable to the increase in the supply of credit, while inflation discourages credit distribution in the WAEMU zone.

In this study, the first hypothesis was that the geographic diversification of bank branches positively affected the credit supply. This hypothesis is accepted because the results of the SDM model reveal that the number of bank branches favors the supply of credit. Concerning the second hypothesis which was that the increase in the size of the bank had a positive influence on the credit supply. This hypothesis is also verified because the results indicate that as the size of the bank increases, banks increase their loan offerings.

## 6. Concluding Remarks

In this study, the main objective is to analyze the spatial dependence of the number of bank branches on the credit supply in the WAEMU zone. The study is carried out from a panel of eight (8) WAEMU countries, over the period 1995-2021 and the choice of this period is due to the availability of data. The results from the SDM model indicate that the size of banks and the number of bank branches positively influence the credit supply in the area, while inflation hurts the credit supply. Such results can lead to a series of economic policy implications. Concerning the positive effect of the number of bank branches on the credit supply, this would represent an opportunity for WAEMU. Indeed, thanks to the entry into force of the single authorization, banks opened new banking branches, which made it possible to increase the credit supply. In short, the WAEMU banking authorities must grant more approval to banks to encourage their entry into the banking network because openness allows established banks to facilitate greater ease in granting credit. Banks in the area must promote the strategy of geographical expansion of their banking branches.

The positive effect of bank size on credit supply allows banks to diversify their activities expand their networks and increase their profits. In addition, when the bank is large, it expands its networks to allow customers to have easier access to credit in their geographic area. Therefore, the monetary authorities must encourage the creation of large banks. Moreover, the increase in the minimum share capital of WAEMU banks, decided on December 21, 2023, from 10 to 20 billion FCFA, aims to strengthen the resilience of the banking sector and respond to the growing financing needs faced by the countries of the Union. They must demand the application of such a measure.

The negative effect of inflation on the supply of credit indicates the adjustment that banks make when the inflation rate increases. Monetary authorities must make efforts to maintain inflation rates at moderate and stable levels.

This study used macroeconomic data which can mask individual and microeconomic realities. This is why a subsequent study, based this time on microeconomic data, will be able to deepen this research.

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